ROLLING BEARING FAULT FEATURE EXTRACTION OF CASING VIBRATION SIGNAL

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Abstract: The health of rolling bearing plays an important part in the operation of rotating machinery like gas turbine engine. Health monitoring and fault diagnosis of rolling bearings based on vibration signals have been through great development these years. But when sensors are set on the casing instead of the bearing pedestal, and the surrounding structure is very complex, the diagnosis problem becomes much more complicated, which brings more challenges to the signal processing. In this paper, a set of signal processing methods are used to enhance and extract the impact features from casing vibration signals, and to realize the detection of rolling bearing faults. A self-adaptive decomposition method called intrinsic time-scale decomposition (ITD) is applied to decompose the vibration signal into a series of proper rotation components and a monotonic trend, helping to extract dynamic features of the signal. Teager-Kaiser energy operator is a simple algorithm calculating the energy of a signal and is very sensitive to transient impact faults. As the fault feature transmitted to the casing is relatively week, autoregressive model (AR) and minimum entropy deconvolution (MED) are to enhance the non-stationary impact components. Experiments are taken on the rotor-bearing-casing test rig with minor defects in the main shaft bearing. Testing on the casing vibration signal, this fault feature enhancing and extracting method shows its remarkable ability in rolling bearing fault diagnosis.

Key words: Casing vibration; fault diagnosis; feature extraction; rolling bearing.

Introduction: The main shaft rolling bearings in a gas turbine engine is precision components and play vital parts in the safe and efficient operation of the whole machine. Thus the condition monitoring and evaluation of rolling bearings and the detection and maintenance for early bearing faults are necessary. There are plenty of vibration-based fault detection and health monitoring methods [1]. But when dealing with casing signals, some special issues must be taken into consideration. Due to the complex interior structure of a gas turbine engine, displacement sensors sometimes cannot be installed inside the machine [2]. Vibration signals will be collected by the accelerometers installed on the casing. It is difficult to analyze casing signals because of the complex surrounding structure and the long path of transmission from the inside to the outside. The vibrational features will be weaker and much noises will be added, which brings more difficulty in the fault diagnosis of bearing faults.

To detect rolling bearing faults needs to extract fault features from the vibration signals. Once the frequency components concerning bearing faults are found during the signal processing, the occurrence of faults could be substantially confirmed. The vibrational features transmitted to the casing will be much weaker than those of the bearing pedestal, so it is preferred to enhance the features for sensitive diagnosis. Autoregressive model (AR) [3] and Minimum entropy deconvolution (MED) [4] are employed in this paper for feature enhancement. AR is a type of statistics and signal processing method describing certain time-varying processes that can predict the deterministic parts in a signal. MED is a signal deconvolution technique whose result highlight a few large spikes and is therefore suitable for the noise reduction of the impact fault signal of the rotating machinery. Because of multiple components and much noise in the vibration signal, signal decomposition is an alternative preprocessing method. Intrinsic time-scale decomposition (ITD) [5] is a self-adaptive decomposition method that can decompose a signal into a sum of components and a monotonic trend. ITD has many advantages over empirical mode decomposition (EMD) [6], a more famous self-adaptive decomposition technique, like higher calculation speed and no such issues in mode confusion, mislocalization of temporal information and phase shifts and distortion. Teager-Kaiser energy operator (TKEO) [7] is an algorithm calculating the energy of a signal, and is very sensitive to transient impact caused by defects. TKEO is used here as an efficient technique for extracting bearing fault features.

In this paper, a rolling bearing fault feature extraction method combining ITD, TKEO, AR and MED is proposed to apply to the casing vibration signal of a rotor-bearing-casing system. The method is tested on experimental signals collected from the rotor-bearing-casing test rig, where rolling bearing faults can be simulated. The qualities of the methods are shown by comparing the relative size of the character frequency components.

Intrinsic time-scale decomposition: Intrinsic time-scale decomposition (ITD) can decompose a signal into a series of components (so called proper rotation components) and a monotonic trend. L is defined as the baseline extraction operator for the signal X_t. With the baseline component L_t extracted from the signal, the proper rotation component H_t is remained. Thus one step of decomposition is done.

$$X_t = LX_t + (1 - L)X_t = L_t + H_t \tag{1}$$

Supposing $\{\tau_k, k = 1, 2, \cdots\}$ local extrema points, set $\tau_0 = 0$. $X(\tau_k)$ and $L(\tau_k)$ are written as X_k and L_k to simplify the expression. Assume that L_t and H_t have definition when $t \in [0, \tau_k]$ as well as X_t having definition when $t \in [0, \tau_{k+2}]$. The piecewise linear baseline extraction operator L is defined on the internal $(\tau_k, \tau_{k+1}]$ between successive extrema as:

$$L = L_k + \left(\frac{L_{k+1} - L_k}{X_{k+1} - X_k}\right)(X_t - X_k) \tag{2}$$

$$L_{k+1} = \alpha\left[X_k + \left(\frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k}\right)(X_{k+2} - X_k)\right] + (1-\alpha)X_{k+1} \tag{3}$$

where $\alpha \in [0,1]$ and usually $\alpha = 0.5$. So the proper rotation component is derived:

$$H_t = (1 - L)X_t = X_t - L_t \tag{4}$$

This method of baseline extraction maintains the monotonicity while a high frequency component known as the proper rotation component is remained. The baseline signal is decomposed again using this method until a monotone trend is derived. So the original signal X_t is decomposed into several high frequency components (proper rotation components) and a trend term. The process can be described as:

$$X_t = H_t + L_t = H_t + (HL_t^1 + L_t^1) = \cdots = H\sum_{k=0}^{p-1} L_t^k + L_t^p \tag{5}$$

where HL_t^k is the proper rotation component and L_t^k the baseline signal, after $(k+1)$ times of decomposition.

Like EMD (empirical mode decomposition) and some other self-adaptive decomposition methods, ITD aims at defining a single component signal whose instantaneous frequency has its physical meaning, and then decomposes the original signal into a series of such single component signals and a trend term. But without repeated iterations, ITD has an advantage over EMD in calculation speed. The ITD also overcomes some of the EMD's limitations, like mode confusion, mislocalization of temporal information and phase shifts and distortion.

Teager-Kaiser energy operator: For continuous-time signal $x(t)$ and discrete-time signal x_n, the Teager-Kaiser energy operator [8] is defined as

$$\Psi[x(t)] = [\dot{x}(t)]^2 - x(t)\ddot{x}(t) \tag{6}$$

$$\Psi[x_n] = x_n^2 - x_{n-1}x_{n+1} \tag{7}$$

The simple harmonic system's total energy is the sum of the kinetic energy and the potential energy. Substituting $x(t) = A\cos(\omega \quad + \phi)$ for x, so

$$E = \frac{1}{2}kx^2 + \frac{1}{2}m\dot{x}^2 = \frac{1}{2}m\omega^2A^2 \propto \omega^2A^2 \qquad (8)$$

And for the sample of the signal of simple harmonic motion $x_n = A\cos(\Omega n + \phi)$, where $\Omega = 2\pi f/f_s$ is the digital frequency, f is the analog frequency and f_s is the sampling frequency of the signal. As the value of Ω is very small, $\sin^2(\Omega) \approx \Omega^2$, so

$$\Psi[x_n] = x_n^2 - x_{n-1}x_{n+1} = A^2\sin^2(\Omega) \approx A^2\Omega^2 \qquad (9)$$

Thus the energy operator can track the energy of any single component signal [9]. Only 3 points are needed when calculating the energy at time n in a discrete-time signal. This algorithm is very simple but has a high temporal resolution, which makes this algorithm sensitive to transient components. When localized defects occur on the outer race, the inner race or the rolling elements, the rotation of the main shaft may cause transient impacts, which excite the natural frequencies of the bearing and the surrounding structure. The vibration signal at this time has components with high amplitude and high frequency. The energy operator approximately equal to the square of the product of amplitude and frequency, which highlights the transient impact. Character frequencies of bearing faults can be identified from the Fourier coefficient of the energy operator result. Then whether the bearing has defects could be determined.

Autoregressive model: Autoregressive model is a type of statistics and signal processing method describing certain time-varying processes. It specifies that the output variable depends linearly on its own previous values and a stochastic term. Applying autoregressive (AR) model on the measured vibration signal could predict the deterministic parts in it. By removing the deterministic parts from the signal, the fault impulses will be enhanced and easier to detect. In the linear prediction process of AR model, the predicted value of the signal at time index k is the linear combination of p prior values,

$$x_k = -\sum_{l=1}^{p} a_l x_{k-l} + e_k \qquad (10)$$

where a_l are the AR coefficients and e_k is the residual error between the linear prediction and the actual measured value. The residual error is mainly white noise if the signal is stationary. But if the signal is non-stationary, the residual error may also contain impulses or other non-stationary components. There are many kinds of algorithms for estimating the AR model, including least squares method and autocorrelation method.

The selection order of the AR model has a large effect on the output. There are several commonly-used criteria for order selection, such as the Akaike information criterion [11]. But since the main purpose of AR model here is to separate the impulses and the stationary components, the criterion could be maximizing the kurtosis of the residual signal, which is conducive to the extraction of bearing fault features. The appropriate model order p should be less than the spacing between two consecutive impulses to guarantee that the impacts will not be adapted by the model to be part of the deterministic signal but remained in the residual signal.

Minimum entropy deconvolution: Minimum entropy deconvolution (MED) uses the maximum kurtosis value as the iteration termination condition, which makes the deconvolution result highlight a few large spikes and is therefore suitable for the noise reduction of the impact fault signal of the rotating machinery. Thus, it could be a good application in bearing [12] and gearbox [13] fault feature extraction.
Suppose the vibration signal of rolling bearing fault,

$$y(n) = h(n) * x(n) + e(n) \tag{11}$$

where $y(n)$ is the actual measured signal, $h(n)$ is the transfer function, $x(n)$ is the impact sequence of the bearing signal, and $e(n)$ is the noise. After a long transmission path and the effects of noise, the impact characteristics may become no longer significant, which means that the fault features are relatively weaker and the entropy of the signal is increased. The objective of MED is to obtain an inverse filter $w(n)$ recovering the input signal $x(n)$ from the output signal $y(n)$,

$$x(n) = w(n) * y(n) \tag{12}$$

$\hat{w}(n)$ is the estimated value of $w(n)$, and its performance is determined by the result $\hat{x}(n)$ of the deconvolution. The closer the shape of $\hat{x}(n)$ is to $x(n)$, the better the result will be. Since the inverse filter is to help $\hat{x}(n)$ restore the original characteristics or most of the characteristics, that is, minimizing the entropy, so this method is called minimum entropy deconvolution. The entropy of the sequence $\hat{x}(n)$ is measured by its kurtosis, which is chosen as the objective function. The optimal result is achieved by selecting the coefficients of MED to maximizing the kurtosis.

$$O_2^4\big(w(n)\big) = \frac{\sum_{n=1}^{N} x^4(n)}{[\sum_{n=1}^{N} x^2(n)]^2} \tag{13}$$

The iteration steps of the MED algorithm can be summarized as follows [14]:

1. Initialize elements of $w^{(0)}$ as 1.
2. Calculate $x(n) = w^{(i-1)}(n) * y(n)$
3. Calculate $b^{(i)}(l) = a\sum_{i=1}^{N} x^3(n)y(n-l)$, where $a = \frac{\sum_{n=1}^{N} x^2(n)}{\sum_{n=1}^{N} x^4(n)}$ and l is the length

of the inverse filter.

4. Calculate $w^{(i)} = A^{-1}b^{(i)}$, where A is the $l \times l$ autocorrelation matrix of the sequence.
5. If $\left\| w^{(i)} - w^{(i-1)} \right\|_2^2$ is smaller than the given threshold, stop the iteration. Otherwise $i = i + 1$ and back to step 2.

Experimental system and data: The rotor-bearing-casing coupled vibration experiment system is designed to simulate vibration faults, and to study transmission characteristics of rotor-bearing-casing system in a gas turbine engine. Figure 1 shows the structural drawing and the photo of the test rig. Accelerators are installed on both the bearing pedestal and the casing.

Rolling bearing faults are simulated on this test rig by replacing the main shaft bearing with fault bearings. The main shaft bearing is NF206EM cylindrical roller bearing. Bearing faults are artificially set by grooving on the surface of the outer race, the inner race and one of the rollers. The size of the defects are 0.3mm width and 0.5mm depth, which is relatively small. According to the character frequency formulas of rolling bearing faults, the character frequencies of outer race, inner race and roller are 5.43f, 7.57f and 5.89f, where f is the rotating frequency of the rotor. Except the main shaft bearing, other experimental conditions are the same. The rotating speed will be set to 1800rpm (30Hz) so the character frequencies are 162.8Hz, 227.2Hz and 176.6Hz.

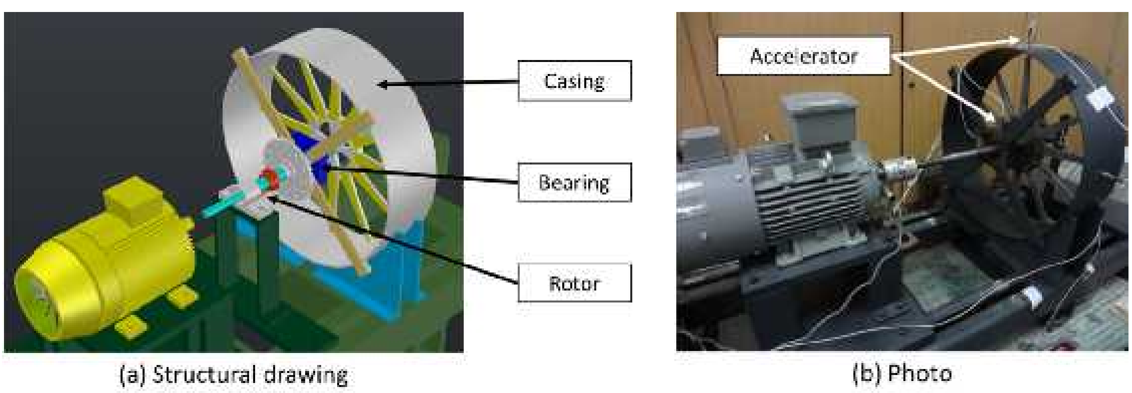


Figure 1: Rotor-bearing-casing coupled vibration experiment system.

Analyzing the vibration signals of the outer race fault as an example, and comparing with the normal bearing. Although the defect is small, the bearing vibration has obvious changes. The time waveform of the bearing pedestal vibration shows more spikes under the condition of outer race fault than no fault. This could be the preliminary judgment of bearing faults. A bearing fault is usually expressed as the high frequency structural resonance modulated by the periodic impact of the defect. Fault features should be demodulated from the vibration signal when detecting bearing faults. Here the Hilbert

transform is employed. The Hilbert envelope spectrum of the bearing pedestal vibration with the normal bearing shows no clear character frequency components. But the components of character frequency and its harmonics and sidebands appear in the envelope spectrum for the outer race fault, which are typical features of rolling bearing faults.
However, fault feature extraction of casing vibration is more difficult than bearing pedestal vibration, since the vibrational features will be much weaker when transmitted from the inside to the outside and more structural vibration and noise will be added. There are not many obvious spikes in the time waveform and character frequency components are hard to see in the envelope spectrum. Further analysis is necessary when there are not bearing pedestal signals but only casing signals.

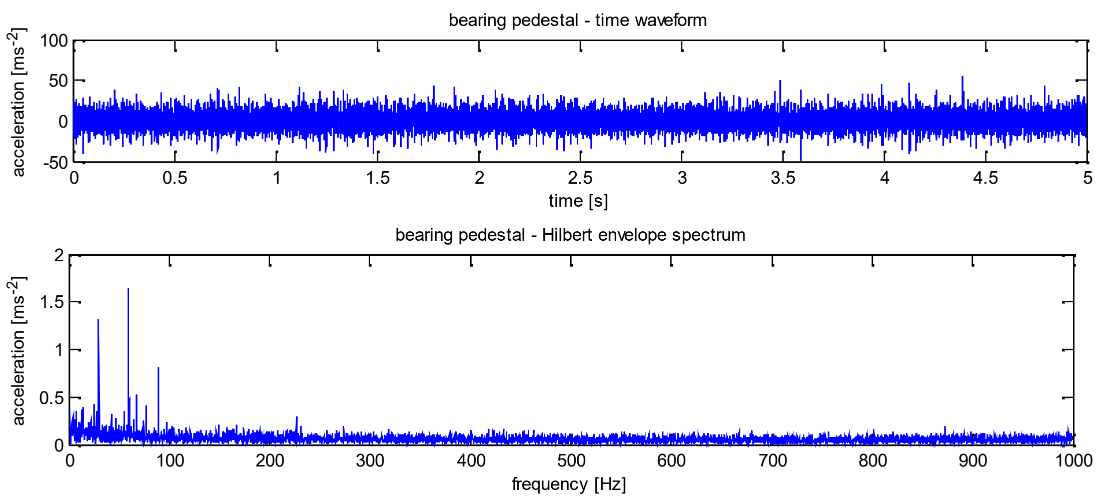


Figure 2: Time waveform and envelope spectrum of bearing signal with no fault.

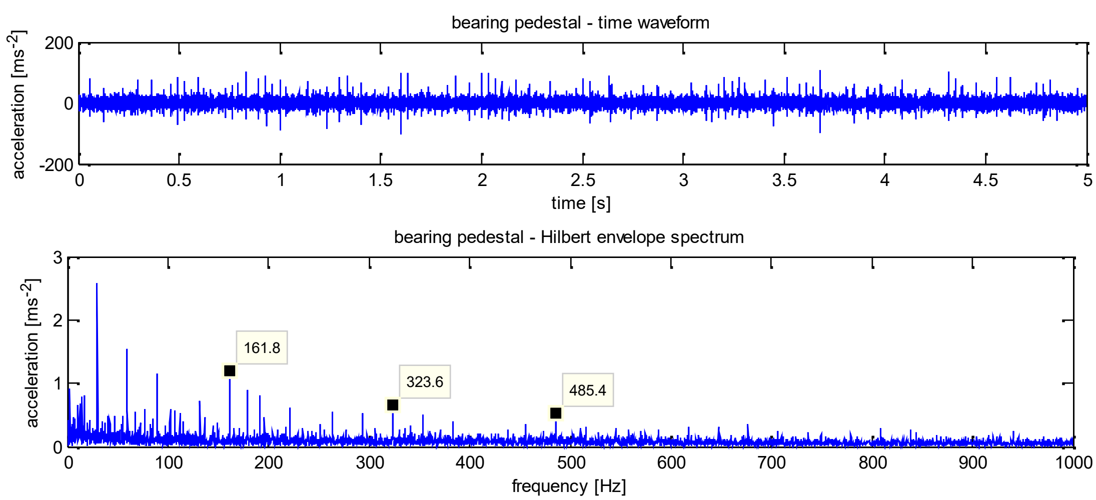


Figure 3: Time waveform and envelope spectrum of bearing signal with outer race fault.

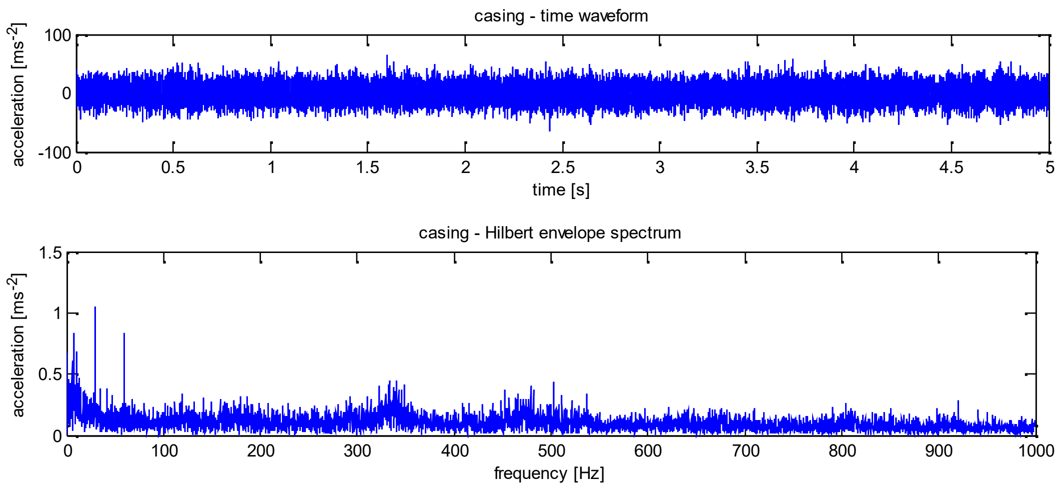


Figure 4: Time waveform and envelope spectrum of casing signal with outer race fault.

Feature extraction based on ITD and TKEO: ITD decomposes the signal into several proper rotation components which are single component signals. So the high-frequency resonance modulated by the fault frequency is more distinct in one of the ITD outputs than in the original signal. Figure 5 displays that the casing signal in decomposed into 11 sub-signals, arranged in descending order of frequency. The modulated features are mostly in the first few sub-signals where the high frequency resonances exist. Figure 6 is Hilbert envelope spectrums of the first 3 ITD sub-signals, where no clear character frequency components can be seen. Instead of envelope spectrum, calculate the Teager-Kaiser energy operator of the sub-signals and take the Fourier transform, and the ITD-TKEO spectrums are in Figure 7. In the first subplot there are 2nd and 3rd harmonic components of character frequency and their side frequencies. Although the features in the ITD-TKEO spectrums are not very prominent, they have been already transmitted to the casing, which show the possibility of bearing fault diagnosis using the casing signal, and prove that TKEO has better capability of highlighting impacts in a signal than Hilbert transform.

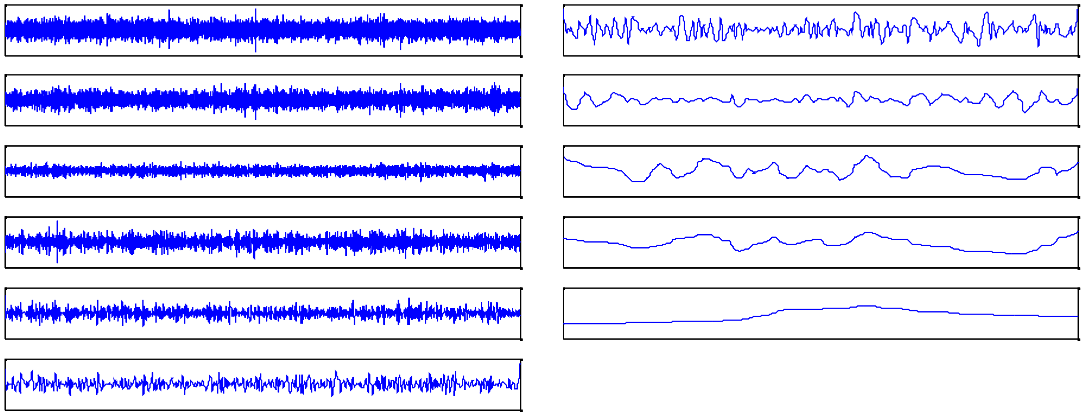


Figure 5: ITD outputs of the casing signal.

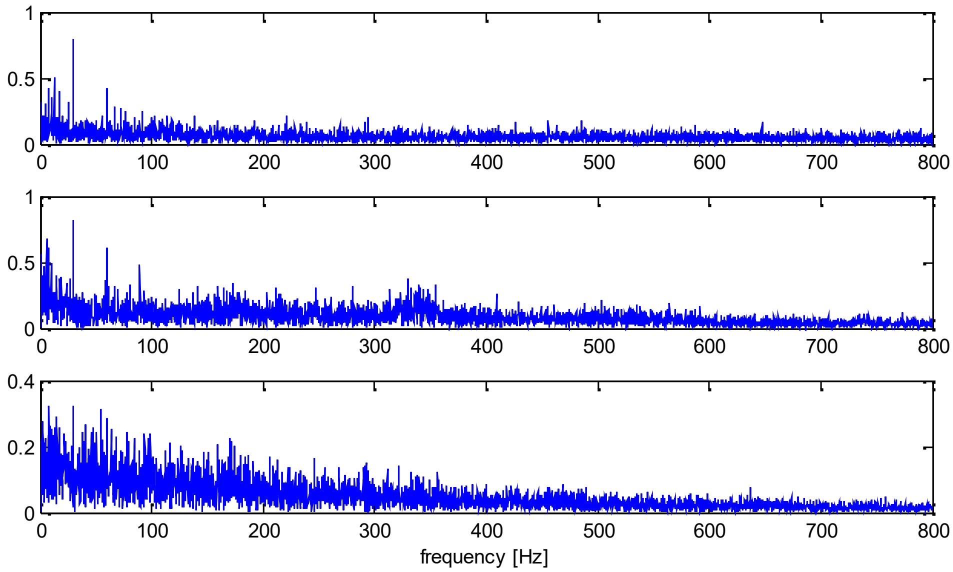


Figure 6: ITD-Hilbert spectrums of the first 3 sub-signals.

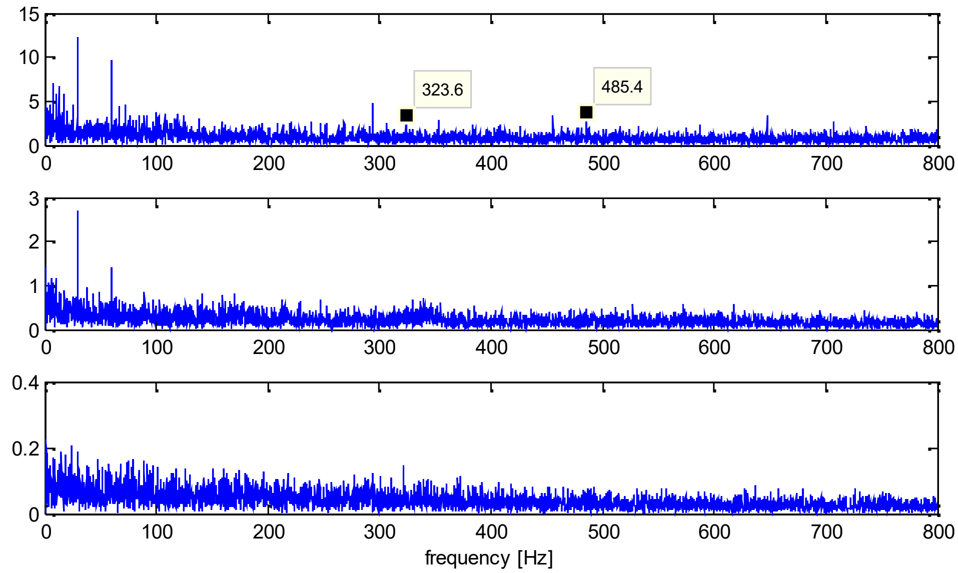
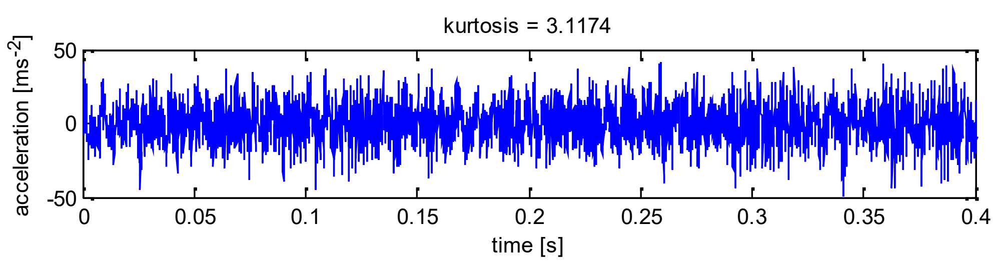


Figure 7: ITD-TKEO spectrums of the first 3 sub-signals.

Feature enhancement based on AR and MED: AR and MED are used to enhance the impulse features in the casing signal. Kurtosis is chosen as an indicator of the impulses, and a bigger value of kurtosis means more significant impulse features. During the optimization for an AR model, kurtosis is also used as an indicator for helping selecting the AR order. Figure 8(a) is the original casing vibration signal whose kurtosis is 3.1174. Figure 8(b) is the residual signal of the AR filter with a kurtosis of 3.9249, which is slightly bigger than the original one. Figure 8(c) is the residual signal of the MED filter with a kurtosis of 7.7049, which has a more significant improvement. And Figure 8(d) is the signal filtered by AR and MED whose kurtosis is 8.4985 and much bigger than the one of the original signal. When the impulses are enhanced and the kurtosis is increased, the spikes are more prominent in the time waveform of a vibration acceleration signal, which is obvious in the figures here.



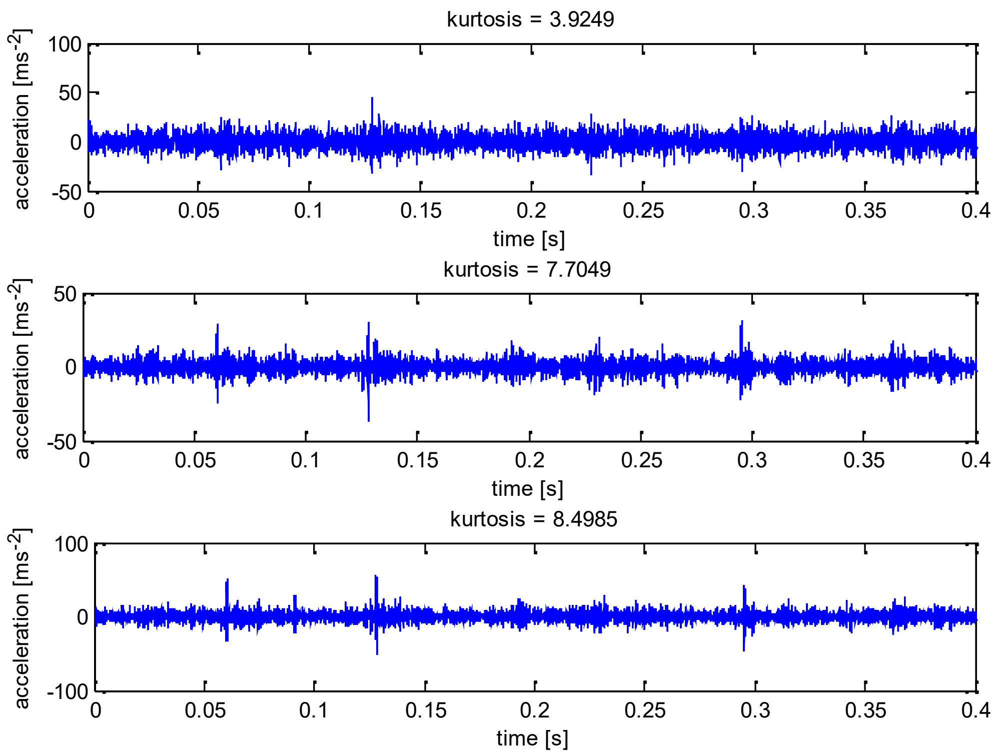


Figure 8: (a) Original casing signal; (b) residual of AR filter; (c) residual of MED filter; (d) residual of AR and MED filter.

Compute the kurtosis for each ITD sub-signal, and the values are in Figure 9. The first 4 high frequency sub-signals have relatively big kurtosis values and could be selected for further analysis since they might carry most of the fault features. Draw an ITD-TKEO spectrum for each of the 4 sub-signals, which are shown in Figure 10. The harmonics of the character frequency and their sideband at the rotating frequency are very clear and much more significant than those components in figures without treatments of AR and MED (Figure 11). That are typical features for the outer race fault of a rolling bearing, and depending on their appearance the existence of a bearing fault could be substantially confirmed.

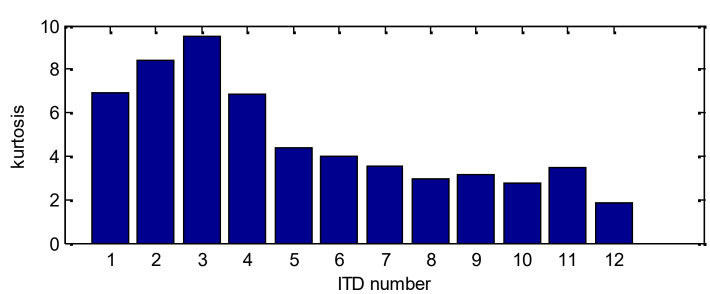


Figure 9: Kurtosis for each ITD sub-signal.

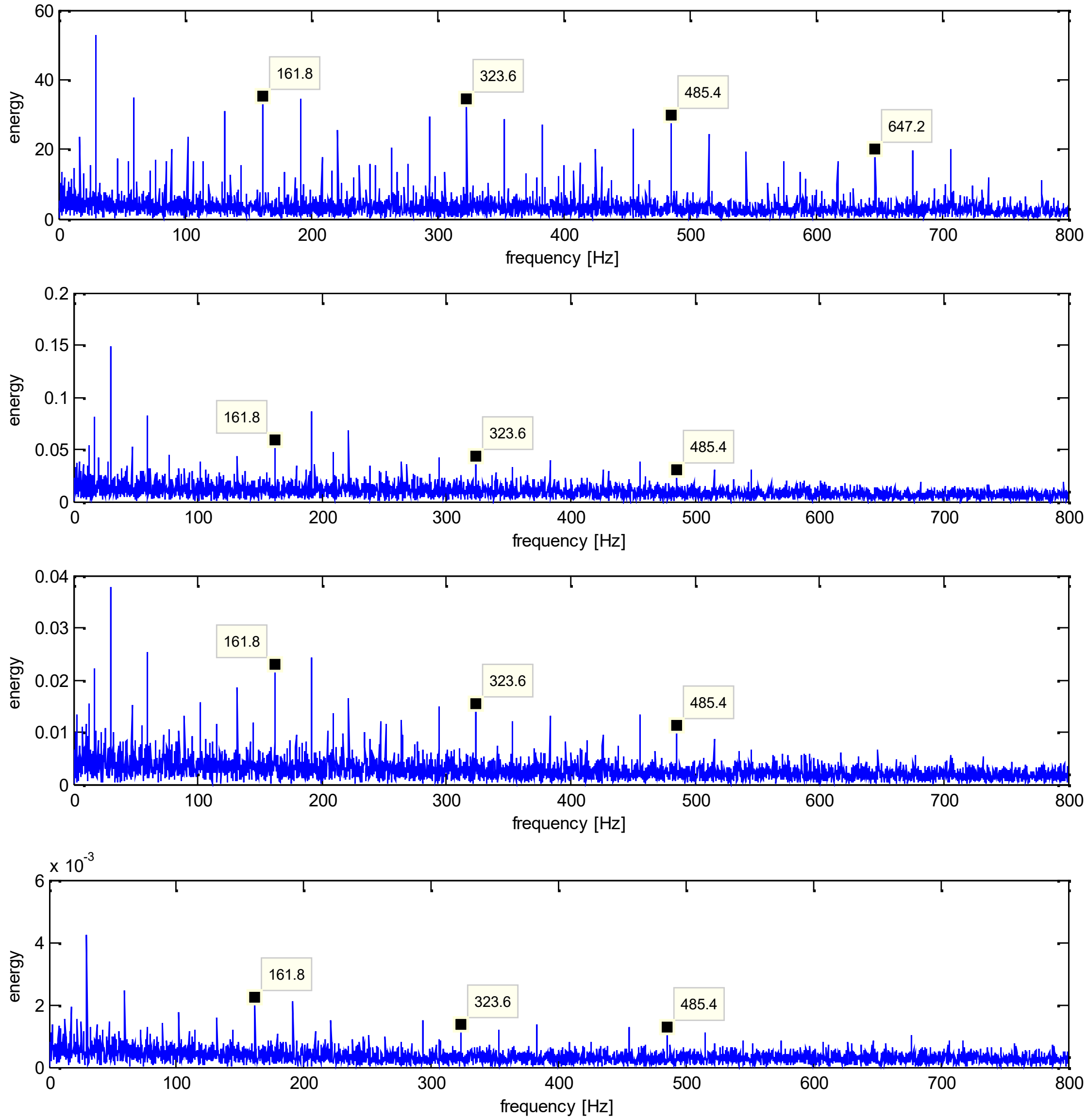


Figure 10: ITD-TKEO spectrums of the first 4 sub-signals with outer race fault.

Draw the ITD-TKEO spectrums of the normal bearing signal as a comparison, which are displayed in Figure. The plots of the first 4 high frequency sub-signals do not show any clear character frequency components, even though they have been processed by the AR and MED method above. This result shows that the deterministic components in a vibration signal will not be enhanced and bring in interference to the diagnosis. Only transient impacts will be enhanced, which will improve the sensitivity of the bearing fault diagnosis method and help to detect minor rolling bearing faults.

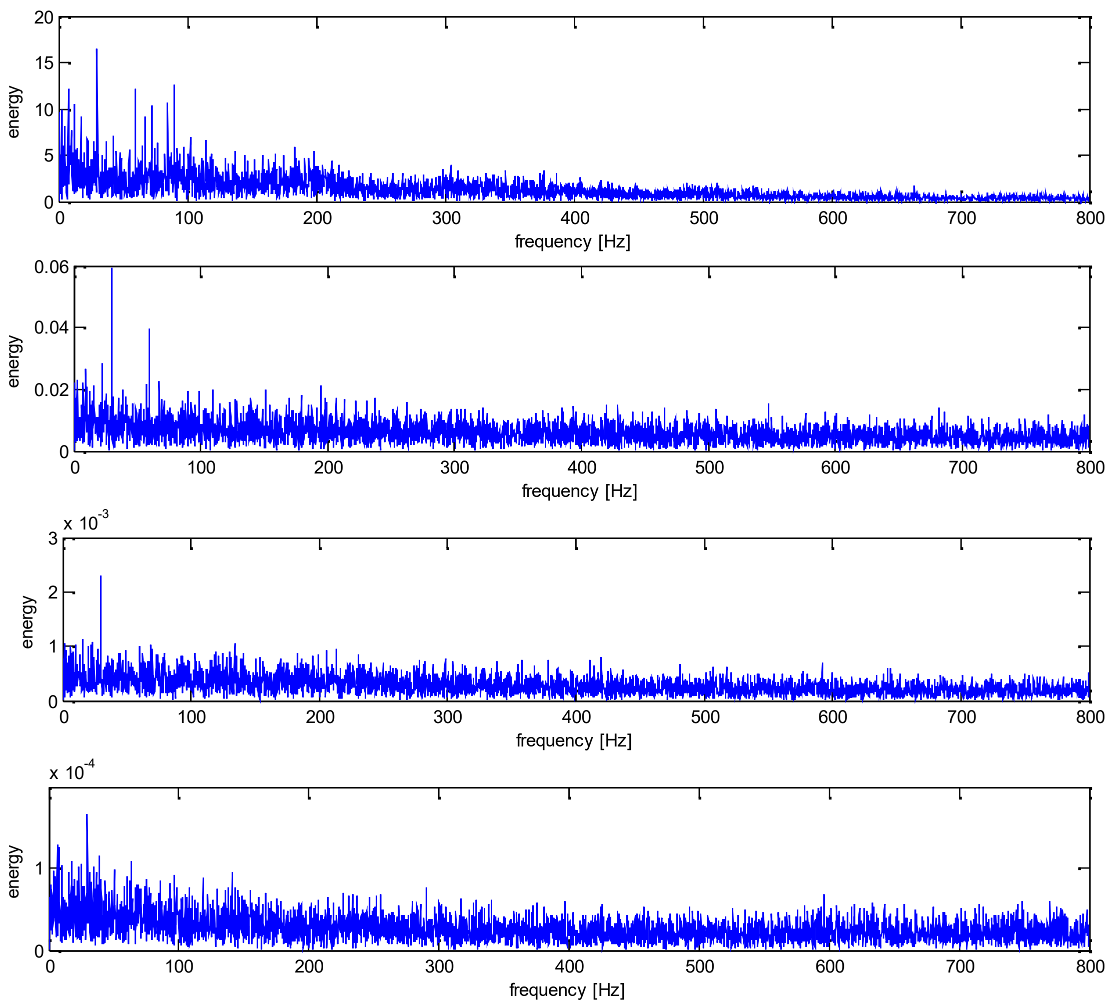


Figure 11: ITD-TKEO spectrums of the first 4 sub-signals with no fault.

Conclusion: This paper presents a feature extraction method for rolling bearing faults in a rotor-bearing-casing system based on the casing vibration signal. The method use AR and MED for feature enhancement and ITD and TKEO for feature extraction. Kurtosis is chosen as indicators for optimization processes since it reflects the strength of the impact components in a signal. Rolling bearing faults are simulated on the rotor-bearing-casing test rig and the experimental signals are used for testing the proposed method. The flow chart of the whole procedure is shown in Figure 12.

This method shows its strong capability in extracting vibrational features of minor bearing faults. The pedestal is close to the bearing and vibration signals collected on it have relatively strong fault features, so the feature extraction is easy as the traditional envelope spectrum based on Hilbert transform could work. But the feature extraction of casing signal is more difficult since the fault features will be weaker and more structural vibration and noise will be added when the vibration is transmitted from the bearing pedestal to the casing. The proposed method has a good performance for this casing signal diagnosis problem, yielding prominent character frequency components.

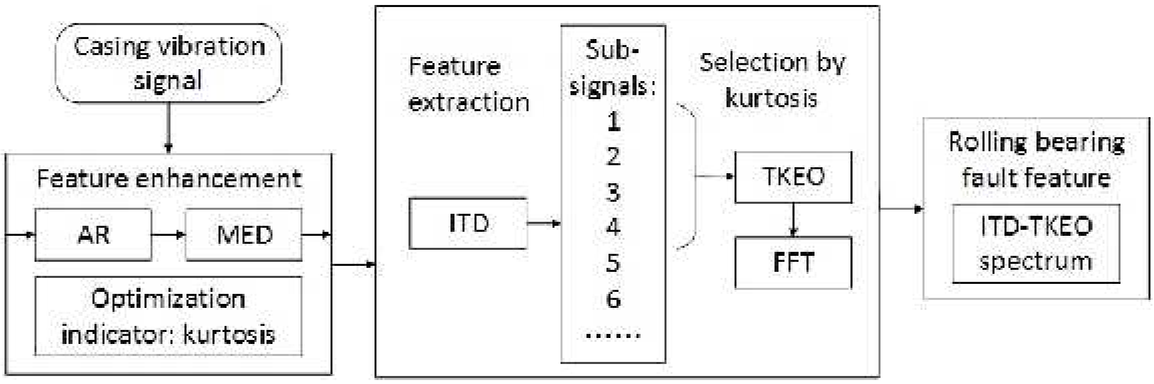


Figure 12: Procedure of the proposed feature extraction method.

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